DESIGN AND DEVELOPMENT OF MODEL TO ENHANCE THE PREDICTION OF PREFERRED LEARNING

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

to

Manav Rachna International Institute of Research and Studies
(Deemed to be University)

by

Virendra Singh
18/Ph.D/099

Under the supervision of
Dr. Parul Gandhi
Professor, Faculty of Computer Applications

FACULTY OF COMPUTER APPLICATIONS

MANAV RACHNA INTERNATIONAL INSTITUTE OF RESEARCH & STUDIES

SECTOR-43, SURAJKUND – DELHI ROAD, FARIDABAD–121001

FACULTY OF COMPUTERAPPLICATION

Certificate

I hereby declare that the short synopsis **"Design and Development of Model to Enhance the Prediction of Preferred Learning"** being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in Computer Applications under faculty of Computer Applications of Manav Rachna International Institute of Research & Studies, Faridabad during the academic year 2021-2022.

It is a bonafide record of original work carried out under the supervision of Dr. Parul Gandhi and has not been submitted in full or part to any other university or institute for a degree or diploma. Further, it is certified that the short synopsis is plagiarism-free and the proof has been submitted.

(Virendra Singh)

18/Ph.D/099

Dr. Parul Gandhi
Professor,
Faculty of Computer Applications

(Chairman, DRC)

(Director, CDP)

ABSTRACT

Adaptive E-learning systems are being used to provide user-specific personalized learning which is mainly based on the learning styles. Questionnaires and surveys were the main techniques for the self-evaluation of the attitude and behavior to know about own learning style in the traditional approach. The traditional approach suffered from the most reasonable fact that the learners were not self-aware of their own preferences due to the state of uncertainty in likings during the learning process. Another drawback of the traditional approach was that learners feel bored and are not serious while filling the questionnaire. Along with that, the traditional approach presumes that the learning style of a particular user is fixed during the whole learning process and can not change when provided with new content or new concepts of learning. The automatic detection of learning styles for a given learning style model (LSM) suffers the problem that mostly LSMs are very old and don't fit in the present educational scenario during and post COVID-19. A proposed LSM that take care of the user's learning styles and interaction behavior with new dimensions will be a nice solution for the adaptive e-learning systems for auto-detection of user's learning styles. This process consists of extracting user log files using a suitable web mining technique and then categorization of these extracted sequences as per the proposed Learning Style Model (LSM) with the help of the clustering algorithm.

Enhanced framework for Adaptive E-learning Systems with an auto-detection capability of learning styles remains a challenge to the research community because of the less concern given to it. An Enhanced framework based on a proposed Learning Style Model implementable using a well-defined clustering algorithm will be proposed in future research work. The proposed adaptive e-learning system will be tested and verified with relevant data sets.

Keywords: Web usage mining, Clustering algorithms, Adaptive E-learning systems(AES), Learning style, Learning Style Model (LSM), Learning Object(LO).

CONTENTS

S.No.	Description	Page No.
1	Introduction	1-2
2	Literature Review	2-7
3	Description of Broad Area	7-8
4	Objectives of the Study	8-8
5	Research Methodology	8-11
6	Expected Outcome of the Research	11
	References	
	Plagiarism Report	

1 INTRODUCTION

In the current era of automation using AI or machine learning, E-learning platforms can help in achieving the desired learning outcome by enhancing the skills and capabilities of the learner. This will help the educational content providers to build such systems that can deliver learning content more efficiently than before. The previous working systems were not that much efficient as they treat every learner possessing the same characteristics and hence provide the learning contents in the same fashion. This static treatment has encouraged the researchers to draw attention to homogenize the architecture of delivering the learning material based on the learner attributes during the learning session. The systems that deliver learning content based on learning characteristics are known as Adaptive E-Learning Systems (AES).

Adaptive E-Learning is the term used for methodologies and mechanisms generated to improve the learning outcome by personalizing the delivery of learning contents based on the learners' attributes constituting their profile. Both researcher and learner agree on the fact that the effectiveness of the learning process increases rapidly when learner profiles are used for the delivery of the learning content (Abdullah et al. 2015). In general, a learner profile may contain the following characteristics like registration id, interest, likings, goals, way of using and adapting learning content, etc. (Brusilovsky and Millan 2007). The key element is to individualize the process of learning keeping an eye on learners' inclinations in learning styles. This individualization exactly tells about the achievement of the specified learner. The learner's attitude, behavior, and likings through the learning session and learning objects describe the learning styles (Honey and Mumford 1992). These learning styles work as static reflectors as these are used to analyze the learner's behavior and attitude how he takes, reacts, and adapts to the learning environment (Keefe 1987).

Numerous theoretical models exist varying on the ways to characterize the learning styles of the learners. It is of great concern to take into consideration that there exist several other tools and classifications methods which are already in use such as Kolb's model (Kolb and Kolb 2005), Felder and Silverman Model (Felder and Silverman 1988), etc. It is worth noting that most of the models are quite similar as their basis is on various stable features such as personality types, cognitive level, environmental preferences, etc.(Cook and Smith 2006). So, the biggest challenge in developing an adaptive E-learning system is to identify the learning style of the learner. Surveys and questionnaires were the main static tools in the traditional way to know about the learning styles when learners self-evaluate their behavior and attitude by filling/answering these tools. The index of Learning Styles1(ILS) is one of the well-known questionnaires that were developed by Felder and Silverman. This suffered from the drawback of considering the learning styles as static during the whole learning process and cannot be altered with time. Secondly, learners are not serious about answering the long questionnaires which require adequate concentration and labor. This type of learning style detection methodology was prepared with a mindset that learners are the best judges of their likings and disliking due to a state of confusion. To highlight these shortcomings, much research has already been done for

auto-detection of learning styles (El Aissaoui et al. 2018) (Feldman et al. 2015) (Latham et al. 2013) (El Alliouin.d.). Even though, how to detect the learning styles effectively is still a matter of open issue to researchers.

Auto-detection of the learning styles has the following three steps:

1. **Web Usage Mining:** Learners' log files are extracted from the webserver using the web mining technique. These extracted files are analyzed as these sequences are taken as learner activities in the learning.

2. **Mapping:** A suitable matching criteria will be carried out from learning objects to a given Learning Style Model. Proposed LSM in our case to find out the learning style of a particular learner.

3. **Auto Detection of Learning Style using Clustering Algorithm:** A suitable clustering algorithm will be launched as the classes of the proposed LSM.

So, the main component of our E-learning system will be Web usage mining, a proposed learning style model, learning objects, and a clustering algorithm auto-detection of learning style and change the mapping between the learning objects and proposed LSM during the learning process to maximize the learning output.

2 LITERATURE REVIEW

According to Azzi, I., Jeghal, A., Radouane, A. (2020), the mechanism to auto-detect the learning styles bring forth a solid foundation to provide the learning contents in a particular learner's personalized way. The classification techniques are considered as the best suitable mechanism for auto-detection of the learning styles by processing the data obtained from learner's activities with the learning system. A robust approach for auto-detection of learning styles must be considered to convert this valuable data into desired information. Hence, to obtain good results the data collection about learners' attitudes and behavior must correspond to different coursework.

According to Khamparia, A., Pandey, B. (2020), there is an increment in the complexity of how to model human behavior in a virtual environment, conventional didactic learning suffers from limitations to provide an adjustable, soft and charismatic e-learning environment. The blending of different learning styles and shortcomings of adaptive and dynamic learning is more productive in terms of improving the performance and cognitive level than conventional learning.

Ouafae El Aissaoui & Yasser El Alami El Madani & Lahcen Oughdir &Youssouf El Allioui (2019) proposed a generic approach for auto-detection of learning styles with respect to a given learning styles model. The two major steps in this approach are, the first step is the usage of web mining

technique to extract the learning sequences of the learner from the webserver as log files and the second step focuses on the classification of these extracted sequences with different categories defined for the learning style model being used incorporated with a clustering algorithm.

Ouafae El Aissaoui& Yasser El Alami El Madani &LahcenOughdir&Youssouf El Allioui(2019) proposed a generic mechanism to auto-detect the learning styles based on the learners' preferences analyzed using the extracted pattern of web mined log files along with suitable machine learning algorithms. Web usage mining techniques are suitable tools to find the relevant patterns in the extracted log files captured as learners sequences in an E-learning environment. The K-modes clustering algorithm then takes these captured sequences as its input. 16 learning style combinations are then formed by the K-mode clustering algorithm on the basis of the Felder and Silverman learning style model. In order to predict the learning style of a learner in real-time naive Bayes classifier is used at the end.

According to O. El Aissaoui, Y. El Madani El Alami, L. Oughdir, and Y. El Allioui, (2018) learning styles are very useful while dealing with an E-learning environment as this helps personalize the learning process. Learners have to fill out a questionnaire when we are interested in knowing the learners' learning style with the traditional approach. This traditional approach is considered as static approach and has many issues. Lack of self-awareness about their likings is one such issue and there is a state of boredom while answering the questionnaire. A generalized approach for auto-detection of learning styles using web usage mining is presented here. This approach classifies learners' log files with respect to a particular learning style model (Felder and Silverman model) using clustering algorithms (K-means algorithm).

According to Silva, Z., Ferreira, L., & Pimentel, A.R. (2017) Learning styles(LS) is the term used to describe the approach of a learner to use the learning contents as per his likings. Every student is unique and posses own way of accessing and adapting the information. So learning styles are most crucial in understanding the preferences. This point helps in get failed while dealing with other learners. Knowledge of learning styles will help in making possible propositions for teaching. So, rationalizing teaching methodologies the learning process adjustable to the individual learners' need is considered as an adaptable one. Here, a structure that will incorporate an adaptable interface for the delivery of learning objects based on the learning style is presented. This will help in the development of the adapted learning object as per learners' learning styles, which will help in the increase of learner's motivation in the use of a learning object as an educational resource.

Klasnja-Milicevic A., Vesin B., Ivanovic M., Budimac Z., Jain L.C. (2017) a platform that gives recommendations to a specific user after analyzing his likes and dislikes, can be considered as a recommender system. This type of system incorporates a specific type of filtering mechanism that tries to provide or recommend particular items such as web pages, news items, music, videos, learning content, etc. This type of system is heavily dependent on the context or domain in which they perform, and it is often not possible to provide a recommendation strategy from one context and then transfer it

to another context or domain. A user-specific recommendation can resolve the problem of information overload as it is capable of filtering the available resources as per the likings and knowledge domain of the user.

Patzer Y, Pinkwart N. (2017) provided a detailed description of both the issues in the LAYA systems. Laya systems that are designed for inclusive e-learning for both the disabled and non-disabled learners suffer from technical accessibility guidelines and educational needs.

N. D. D. Mendez, V. T. Morales and R. M. Vicari, (2016), described metadata as one of the main the characteristic of the LO. The metadata attached with a LO is not only used to describe the LO but also makes it easy to search and retrieve from the database. This metadata possesses certain properties that help in individualizing and identifying each LO. Metadata describes the know-how, its developer and development information, the section of memory to which it is indexed, implementation, interactivity, technical specifications and other relevant information. All these help understand its contents. The primary purpose of attaching this information as metadata is to search, assess, recovery, and use of LOs. This also facilitates the reuse of these LOS. The main objective is to personalize the assessment criteria of LOs as per the learning style of a particular learner.

According to Deborah, L.J., Sathiyaseelan, R., Audithan, S. (2015) utmost care should be taken while predicting the learning styles as these are not fixed and may suffer from slight to drastic variation due to psychological imbalance, time, mood, and other constraints. So, the parameters used to know about the learning style prediction are uncertain. To handle this type of uncertainty, Felder–Silverman learning style model is taken as a suitable model for learning style prediction along with Fuzzy rules that are capable of dealing with the uncertainty in the learning style predictions.

Manal Abdullah, Reem M. Bashmail, Wafaa H. Daffa, Mona Alzahrani & Malak Sadik**,** (2015) described the significant differences of the individual learner's capabilities and way of adapting the learning contents i.e. learning styles brought individual learning outcomes. With the rapid development in the field of E-learning technologies, it is possible to provide a more efficient learning environment in which learner can enhance their learning outcome. How learning styles bring positive impact on learners' outcomes would be analyzed and this analysis would help make recommendations for developers and users of the online course contents. E-Learning platform Blackboard learners' performance data is used to carry out data analysis.

In order to, Icoz, Kutay; Sanalan, Vehbi A.; Ozdemir, Esra Benli; Kaya, Sukru; Cakar, Mehmet Akif, (2015), create a personalized learning environment framework, the focus should be on the following three tasks: first is to develop the outlook or ontologies for the course material, second is to the way of measuring the cognitive level about the concepts and the third is to provide individualized recommendations to create an individualized learning environment. An intelligent recommendation module that is assisted with learners' data with integrated ontologies is used for the development of the E-Learning system. This system makes a comparison between learners' mind maps while dealing

with the e-learning environment and the suggestions coming from the recommendation module.

Mofreh A. Hogo, (2010) made a classification of learners on the basis of their profiles. Hogo named these classes as regular, workers, casual, bad, and absent. The strategy adopted for the development of e-learning systems is based on the data coming from statistical usage patterns. It attempted to find the solution of how to overcome the problem of the bad students who are away back to be regular ones. It tried to evolve a mechanism that has the capability of evaluating the learners along with establishing a strategy in which content and structure of the e-learning system become adaptable. Learners' profile was determined the application of different fuzzy clustering techniques (FCM and KFCM).

Hogo, Mofreh. (2010) attempted to classify the learners into different categories and predict their profiles using different fuzzy clustering techniques. Various phases related to data definition, gathering, and formation, features selection along with experiments design using different fuzzy clustering models were described for a better understanding of the working environment. In comparison, it was found that Fuzzy clustering provides a more accurate reflection of the learners' behavior than that of crisp clustering. It was also found from the comparative analysis that the KFCM gives much better results than FCM when used for predicting the learners' behavior.

Castro Espinoza, Felix &Vellido, Alfredo & Nebot, Angela. (2007) introduced a classification for various e-learning problems when using Mining Data techniques. These problems involve the following parameters: learners' classification on the basis of their learning outcome, irregularity in learning interaction, classification of the interaction for the design of the navigation map, possible clustering mechanism to similar usage of the e-learning system, individualized adaptability of the system as per capability and requirements of a specific learner, etc. Different modeling techniques are used from the references like Neural Networks, Genetic Algorithms when we have to provide a reasonable organization of the available bibliographic information from the Data Mining practitioner's point of view. With the same strategy, data is also arranged while dealing with the Data Mining problems like clustering, classification, prediction, etc.

Bernice McCarthy,(1997) defined the different aspects of learning. His classification was based on both sides of the coin which made it complete and one side could not serve all the purpose. Learning can be both reflective and active, verbal and nonverbal, concrete and abstract, head and heart. The focus of the classification was based on the fact how students convert the different instructional methods given by the teacher into personally meaningful information. It characteristicdepends on the learner to take the information and bring out more productive outcomes. Learners were divided into four groups as 1. Imaginative, 2. Analytic, 3. Common sense and 4. Dynamic.

Sanjuan, Oscar & Pelayo Garcia-Bustelo, B. & Gonzalez Crespo, Ruben & Franco, Enrique. (2009) presented a description on the use of the Internet as a medium for educational learning as it brought a rapid development in technologies and access to the desired information have become easier than before but it also raised new issues to the learning process. One suitable example of these issues is how to navigate the learner while interacting with an online learning environment. Learners are expected to have support either from their tutor or peer fellows during a learning session. To resolve

such types of issues some recommendation strategies are in existence. Recommendation System made an attempt to ease out the process of learner based on the analysis of his interactive activities or from the data gathered from the activities of the learners having similar features.

As per Saul McLeod (2013) teachers are responsible for what a learner learns so a teacher should keep an eye on the activities that are designed and carried out in such a way to maximize the learning outcome. The learning outcome will be maximum only when learners have the facility to interact with the material that suits them best. Personalization of learning activities will be more productive when it has the capability to identify the lesser preferred learning styles and has the ability to strengthen these styles with the use of the experiential learning cycle. The experiential learning cycle has four phases as follows: 1. Concrete Experience, 2. Reflective Observation of the New Experience, 3. Abstract Conceptualization, and 4. Active Experimentation. When there is weakness at either level then the rotation policy of the experiential learning cycle strengthens at that level.

According to Markellou, Penelope & Mousourouli, Ioanna & Sirmakessis, Spiros & Tsakalidis, Athanasios. (2005) Semantic Web Mining technology's technical challenge in the e-Learning domain may relate to the provision of personal user experience. These tools take care of the personalized requirements and needs of the learner. It is distinguishable at two stages as offline and online. The offline stage involves data preparation, logic creation and web usage mining. On the other hand, the online stage takes care of the production of personalized recommendations as per requirements. These two stages when integrated help in proposing a personalized learning scenario that uses Semantic Web vision by using ontologies with Using Mining techniques to provide the learning contents as per the requirements of learners.

According to Romero, Cristobal & Ventura, Sebastian. (2006), although several types of research have already been done in the field of e-learning and claimed to enhance the level of understanding of the learner, none of the research ever revealed the influence of cognitive styles with system characteristics which increase the degree of user satisfaction. It is a fact, sincere care had been taken while conducting the empirical research but the results are inconsistent when establishing a relationship among design related to information system (IS) satisfaction, as well as the determinants of IS satisfaction. So a thorough understanding of IS satisfaction still remains puzzling.

Sekhavatian, Ailar & Mahdavi, Mehregan. (2011) showed that the experimental results indicate that the proposed system increased weak students' success rate by making good recommendations, as well as for strong students in order to enhance their performance.

Herman Dwi Surjono, (2011) described the two learning style models as helpful in acquiring the system’s adaptivity. The two learning style models: are VAK and Felder. The VAK learning style model describes the three types of learners as visual, auditory, and kinesthetic. On the other hand, the Felder model describes the two learning styles as global and sequential.

Brusilovsky P., Millan E. (2007) described the constructional design of an adaptive e-learning system giving preference to learners profile. It describes the various approaches incorporated for user modeling in adaptive web systems, the effective mechanism for the storage of the user data, how to handle the current state of the user.

Kristensen, Terje, (2016) presented an analysis of the approaches used for adaptive construction of the learning objects that take care of the various elements that have the capability to influence the expected outcome of the objectives like motivation, expectation, learner's style, a priori knowledge.

Dwivedi, Pragya; Bharadwaj, Kamal K, (2013) presented a mechanism that has the ability to integrate both learning styles and the knowledge level of the user to effectively provide learning recommendations. A weighted hybrid scheme was proposed capable of firstly recommending the right learning resources to a learner keeping a mechanism of incorporating both the learners' learning styles (LSs) and the knowledge levels (KLs). Then by establishing trust values among learners, a weightage mechanism for recommendation works in such a way that trustworthy learners having greater knowledge and similar learning style patterns will have greater weightage than that of a given active learner.

Benhamdi, Soulef; Babouri, Abdesselam; Chiky, Raja, (2017) collaborative and content-based filtering mechanism is used to provide a new approach for recommendation: NPR_eL (New multi-Personalized Recommender for e-Learning).

3 DESCRIPTION OF BROAD AREA

Here, we will describe about important concepts on which adaptive e-learning methodologies relies on. These are as given below:

1) Web Usage Mining (WUM),
2) Learning Style Model (LSM),
3) Proposed Learning Style Model,
4) Learning Object (LO) and
5) Clustering algorithm.

Web Usage Mining: The process of accessing and identifying the web usage pattern from websites is known as web usage mining (Cooley et al. 1997)(Mobasher2006). The extracted files are analyzed to identify the learner's navigational pattern and behavior. These extracted files contain the log files having the information related to how learners access the learning objects stored on the web servers. Web log files are plain text files that contain raw data about learner activities (Facca and Lanzi 2003).

There are mainly three steps involved in the usage mining process (Cooley et al. 1999):

1) **Data Pre-processing:** This process involves cleaning of data and then converting it into a meaningful pattern which can be further analyzed easily.

2) **Pattern Discovery:** This process involves obtaining background information and patterns from the data obtained from the previous step with the help of machine learning and data mining techniques.

3) **Pattern Analysis:** This step involves taking out the relevant patterns from the output of previous step.

Learning Style Model: Every adaptive e-learning system has the learning style model as its main component(Riad et al. 2009),. The e-learning system provides recommendations for delivering the learning objects based on the characteristics defined within a learning system used (Murray and Pérez 2015). A learning style model has learning style as one of the main components because it is used to describe learner's behavior, the preferred way of the learner to grasp and treat the learning object (Kolb and Kolb 2005) (Curry 1981). Learning styles are used to define the different dimensions of a learning style model.

Proposed Learning Style Model Model: In mostly AES, the Felder and Silverman Learning Style Model (FSLSM) is used as the most appropriate learning style model to implement the e-learning systems as discovered by previous (Graf and Kinshuk2009) (Kuljis and Liu 2005). In our work, we will use a proposed LSM that will be best suitable in the current educational scenario. It consists of four dimensions and each dimension is further having two categories. The virtual dimension has live and downloaded as two categories, the sustained dimension has continuous and discontinuous as two categories, the enthusiastic dimension has theoretical and experimental as two categories while the fourth, potential dimension has been categorized into supervised and unsupervised.

Live (L) learners obtain the desired learning material by direct interaction in live sessions, on the other hand, Downloaded (D) learners use the learning contents after downloading.

Continuous (C) learners tend to use materials in a step-by-step manner. While Discontinuous (D) learners use materials in a scattered way that provide summarized and theoretical information and understand the concept holistically and then search for further possibilities.

Theoretical (T) learners prefer to have focus only on the course material. While the Experimental (E) learners focus more on the concept and then think out of the box for real-life experiments.

Supervised (S) learners are intituional type and have limited knowledge but do fully utilization of resources. On the opposite, the unsupervised (U) learners have unlimited knowledge but do limited utilization of resources.

4 OBJECTIVES OF THE STUDY

PROBLEM STATEMENT

In the current era of technology, learner characteristics are not fixed and vary with the passage of time, pace, perception and acceptability. It is not easy to say that a learner has completely discarded a particular learning object data type or may not like with the passage of time or with an increase in his cognitive level. The existing technology used for auto detection of the learning styles is based on the old learning style models that doesn't fit in the current scenario of online learning during and post COVID. So there is a need for a new Learning Style Model that can be implemented in e-learning systems to handle the changing behavior and degree of acceptance of learning objects to maximize his achievements/success.

RESEARCH OBJECTIVES

1. To identify the pattern of accessing the learning contents based on the log files extracted from the web server using a web mining technique.
2. To propose a Learning Style Model (LSM) and map with learning objects (LO).
3. To apply appropriate clustering algorithms on proposed model to enhance the prediction of the varying learner characterstics.
4. To validate the proposed model using a real-time dataset.

RESEARCH METHODOLOGY

5.1. To identify the pattern of accessing the learning contents based on the log files extracted from the web server using a web mining technique.

The proposed research will include the identification of the learning pattern based on learners' interaction with the system during a session. Learner's log files were extracted with a specific web usage mining technique (WUM) and analyzed for pattern discovery. This pattern will tell about the behavior (learning style) of accessing the learning content during that session. The learner's learning style will depend on the proposed learning style model as shown in Fig.1. The relevant learning sequences can be mapped with one of the particular learning style combinations of the proposed LSM as shown in Fig.2.

5.2. Propose a Learning Style Model (LSM) and map with learning objects (LO).

An LSM will be proposed with certain dimensions to effectively categorize the learning styles identified from the discovered pattern of web logged files. The dimensions will form the arms of the proposed model and these arms may further be divided into subcategories as shown in Fig.1. These subcategories will form the whole set of learning styles that learners can acquire. This whole set is then divided into possible sets of clusters.

These clusters are then mapped with the learning objects (LO) based on the possible combination of the proposed LSMs feature values. The clustering algorithm is then supplied with feature values of the proposed LSM and relevant processed patterns of the learning sequences as input. Learner sequences are then grouped based on LSM feature values.

The acquired learning style of a learner is not fixed and with the passage of time, pace, and cognitive level, it may vary so the clusters are needed to be modified with the help of the clustering algorithm which will provide pace to the learning process and ensure an increase in the rate of success in terms of coursework outcome.

5.3 Clustering Algorithm

The clustering algorithm will take the learner's sequences and mapped learning style categories as input and provide possible clusters or classes that will effectively manage the changing behavior toward a learning object as shown in Fig.2.

5.4 Data Sources and Evaluation Methods

Secondary Data Sources: It will be taken up from the different research papers and peer-reviewed journals on Education, Computer Science & technology, AI and Machine Learning etc.

Primary Data Sources: It will be generated by conducting a physical test of the proposed system with a predefined set of students on campus.

Evaluation Methods: It may be the same as that the previous researchers have taken up to conclude their task or new ones and the final outcome may be in the form of comparative analysis.

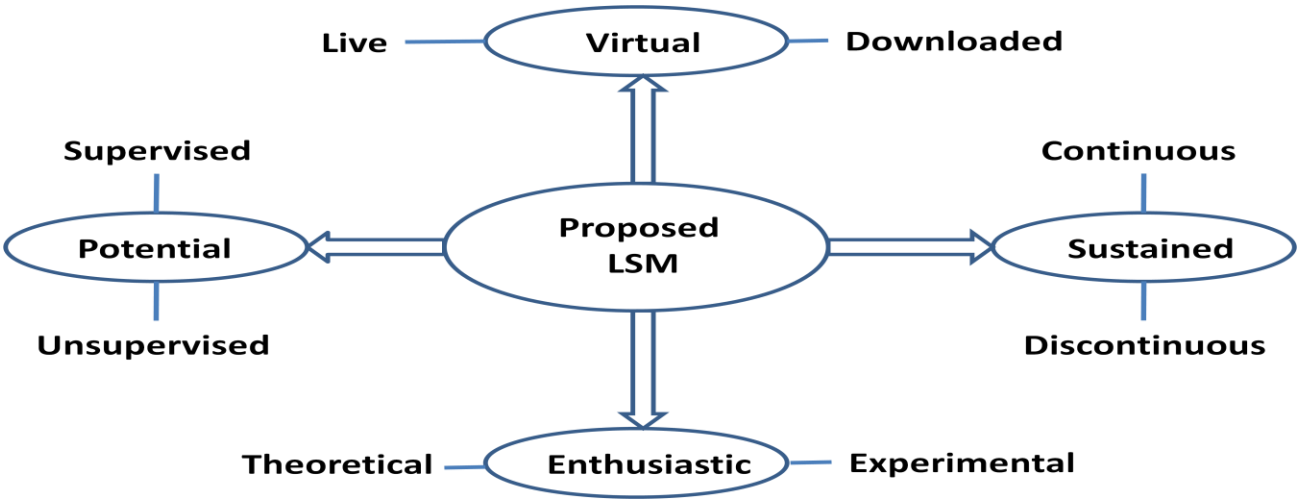

Fig.1: Proposed LSM with four Dimensions and two categories for each dimension (Source: Self)

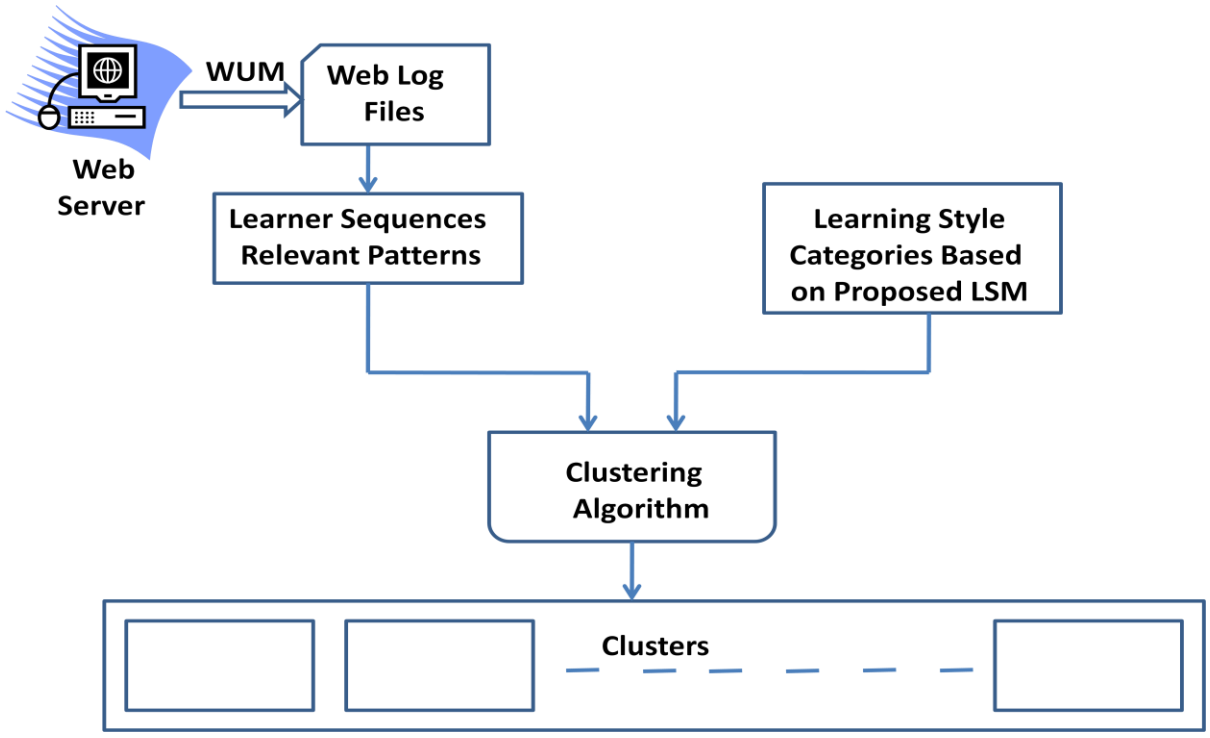

Fig.2: Workflow Diagram of the Research Methodology (Source: Self)

5 EXPECTED OUTCOME

The research will provide a frame to design an enhanced e-learning system that will incorporate user's preferred learning style based on a proposed learning style model LSM. The proposed LSM will provide a new way to implement effective mapping between learning objects and learning styles of the learner as per his every interaction with the learning environment and will incorporate better learning contents and higher rate of success.

REFERENCES

Abdullah, Manal & Sadik, Malak. (2015). The Impact of Learning Styles on Learner's Performance in E-Learning Environment. IJACSA International Journal of Advanced Computer Science and Applications. 6. 24 -31. 10.14569/IJACSA.2015.060903.

Abdullah, M., Bashmail, R. M., Daffa, W. H., Alzahrani, M., & Sadik, M. (2015). The impact of learning styles on Learner's performance in E-learning environment. International Journal of Advanced Computer Science and Applications, 6(9), 24–31.

Abdullah, M. A. (2015). Learning style classification based on student's behavior in moodle learning management system. *Transactions on Machine Learning and Artificial Intelligence*, *3*(1), 28.

Albatayneh, Naji & Imran, Khairil & Chua, Fang-Fang. (2018). Utilizing Learners' Negative Ratings in Semantic Content-based Recommender System for e-Learning Forum. Educational Technology & Society. 21.

Albatayneh, N. A., Ghauth, K. I., & Chua, F. F. (2014). A Semantic content-based forum recommender system architecture based on content-based filtering and latent semantic analysis. In Recent Advances on Soft Computing and Data Mining (pp. 369-378). Cham, Switzerland: Springer International Publishing. doi:10.1007/978-3-319-07692-8_35

Almohammadi, K. a., Alzahrani, A., Alghazzawi, D., & Aldabbagh, G. (2017). A type-2 fuzzy logic recommendation system for adaptive teaching. *Soft Computing*, *21*(4), 965–979.

Azzi, I., Jeghal, A., Radouane, A. *et al.* A robust classification to predict learning styles in adaptive E-learning systems. *Educ Inf Technol* 25, 437–448 (2020).

Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), The Adaptive Web. Heidelberg: Springer, Berlin.

Castro, F., Vellido, A., Nebot, À., & Mugica, F. (2007). Applying data mining techniques to e-learning problems. In L. C. Jain, R. A. Tedman, & D. K. Tedman (Eds.), Evolution of Teaching and Learning Paradigms in Intelligent Environment (Vol. 62) (pp. 183–221). Heidelberg: Springer, Berlin.

Capuano, N., Gaeta, M., Ritrovato, P., & Salerno, S. (2014). Elicitation of latent learning needs through learning goals recommendation. Computers in Human Behavior, 30, 663-673.

Chang, Y.-C., Kao, W.-Y., Chu, C.-P., & Chiu, C.-H. (2009). A learning style classification mechanism for elearning. Computers & Education, 53(2), 273–285.

Ciloglugil, B. (2016). Adaptivity based on felder-silverman learning styles model in e-learning systems. *4th International Symposium on Innovative Technologies in Engineering and Science, ISITES*, (pp. 1523–1532).

Cook, D. A., & Smith, A. J. (2006). Validity of index of learning styles scores: Multitrait-multimethod

comparison with three cognitive/learning style instruments. Medical Education, 40(9), 900–907.

Dascalu, M. I., Bodea, C. N., Moldoveanu, A., Mohora, A., Lytras, M., & de Pablos, P. O. (2015). A Recommender agent based on learning styles for better virtual collaborative learning experiences. Computers in Human Behavior, 45, 243-253.

Drachsler, H., Verbert, K., Santos, O. C., & Manouselis, N. (2015). Panorama of recommender systems to support learning. In Recommender systems handbook (pp. 421-451). Boston, MA: Springer US.

Dwivedi, P., & Bharadwaj, K. K. (2013). Effective trust-aware e-learning recommender system based on learning styles and knowledge levels. Educational Technology & Society, 16(4), 201-216.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2011). Collaborative filtering recommender systems. Foundations and Trends in Human-Computer Interaction, 4(2), 81-173

El Aissaoui, O., El Madani El Alami, Y., Oughdir, L., & El Allioui, Y. (2018). Integrating web usage mining for an automatic learner profile detection: A learning styles-based approach. In 2018

El Aissaoui, O., El Alami El Madani, Y., Oughdir, L. *et al.* (2019). A fuzzy classification approach for learning style prediction based on web mining technique in e-learning environments. *Educ Inf Technol* 24, 1943–1959 (2019).

EL AISSAOUI, O., EL MADANI, Y. E. A., OUGHDIR, L., & EL ALLIOUI, Y. (2019). Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles. *Procedia computer science*, *148*, 87-96.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. Engineering Education, 78(7), 674–681

Feldman, J., Monteserin, A., & Amandi, A. (2015). Automatic detection of learning styles: State of the art. Artificial Intelligence Review, 44(2), 157–186.

Ghauth, K. I. B., & Abdullah, N. A. (2011). The Effect of incorporating good learners' ratings in e-learning content-based recommender system. Educational Technology & Society, 14(2), 248-257.

Honey, P., & Mumford, A. (1992). Book reviews: The manual of learning styles. Management Learning, 14(2), 147–150.

Icoz, Kutay & Sanalan, Vehbi & Çakar, Mehmet & Ozdemir, Esra & Kaya, Sukru. (2015). Using Students' Performance to Improve Ontologies for Intelligent E-Learning System. Educational Sciences: Theory and Practice. 15. 1-12. 10.12738/estp.2015.4.2645.

Jalal, A., & Mahmood, M. (2019). Students' behavior mining in e-learning environment using cognitive processes with information technologies. *Education and Information Technologies*, 1–25.

Keefe, J.W. (1987). Learning style: Theory and practice. National Association of secondary school principals.

Khamparia, A., Pandey, B. Association of learning styles with different e-learning problems: a systematic review and classification. *Educ Inf Technol* 25, 1303–1331 (2020).

Klasnja-Milicevic A., Vesin B., Ivanovic M., Budimac Z., Jain L.C. (2017) Recommender Systems in E-Learning Environments. In: E-Learning Systems. Intelligent Systems Reference Library, vol 112. Springer,Cham.

Kolb, A. Y., & Kolb, D. A. (2005). The Kolb Learning Style Inventory—Version 3 . 1 2005 Technical Specifications. LSI Technical Manual, 1–72.

Latham, A., Crockett, K., & Mclean, D. (2013). Profiling Student Learning Styles with Multilayer Perceptron Neural Networks. In 2013 IEEE International Conference on Systems, Man, and Cybernetics (pp. 2510– 2515).

Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. In Recommender systems handbook (pp. 73-105). Boston, MA: Springer US

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A Survey. Decision Support Systems, 74, 12-32.

Munoz, A., Lasheras, J., Capel, A., Cantabella, M., & Caballero, A. (2015). OntoSakai: On the optimization of a learning management system using semantics and user profiling. Expert Systems with Applications, 42(15), 5995-6007.

Murray, M. C., & Pérez, J. (2015). Informing and performing: A study comparing adaptive learning to traditional learning. The International Journal of an Emerging Transdiscipline, 18(1), 111–125

Patzer, Yasmin & Pinkwart, Niels. (2017). Inclusive E-Learning - Towards an Integrated System Design. Studies in health technology and informatics. 242. 878-885.

Santos, O. C., Boticario, J. G., & Pérez-Marín, D. (2014). Extending web-based educational systems with personalised support through user centred designed recommendations along the e-learning life cycle. Science of Computer Programming, 88, 92-109.

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., & Duval, E. (2012). Context-aware recommender systems for learning: a survey and future challenges. IEEE Transactions on Learning Technologies, 5(4), 318- 335.